



## **Load Management in an Intelligent Office Building Using Model Predictive Control Strategy**

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*Publication date:*  
2010

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*Citation (APA):*

Zong, Y. (Author). (2010). Load Management in an Intelligent Office Building Using Model Predictive Control Strategy. Sound/Visual production (digital)

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# Load Management in an Intelligent Office Building Using Model Predictive Control Strategy

Yi Zong

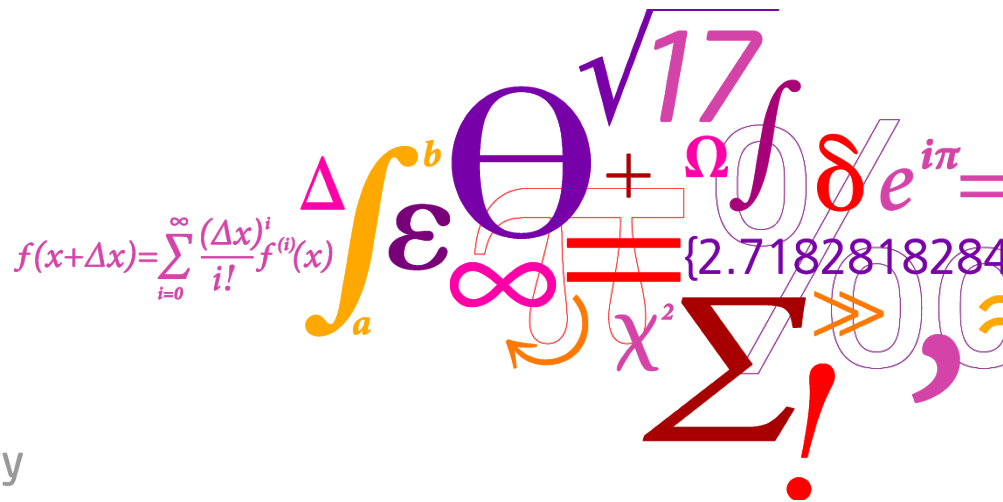
Intelligent Energy Systems

November 2<sup>nd</sup>. WES Workshop

Risø DTU

National Laboratory for Sustainable Energy

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# Outline

- Introduction
- **SYSLAB**-Distributed Power System Platform
- **PowerFlexhouse**-Intelligent office building
- Model predictive controller
- Results
- Future work
- Conclusions

# Introduction: Power Systems with high penetration of Wind

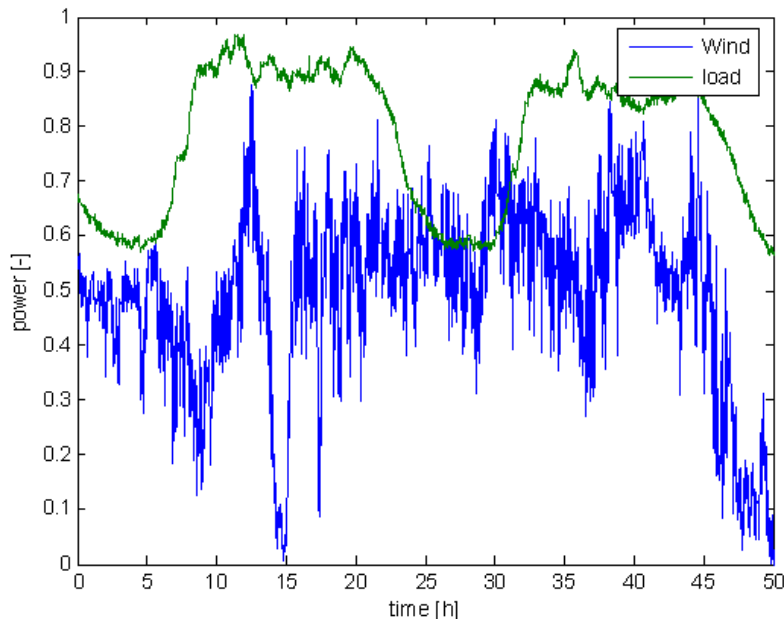


Fig. 1. Load and wind power variations

Integration of **50%** wind energy into electricity system by 2025 in Denmark

## Issues with wind

- Fluctuations
- Variations
- Predictability

**Production**

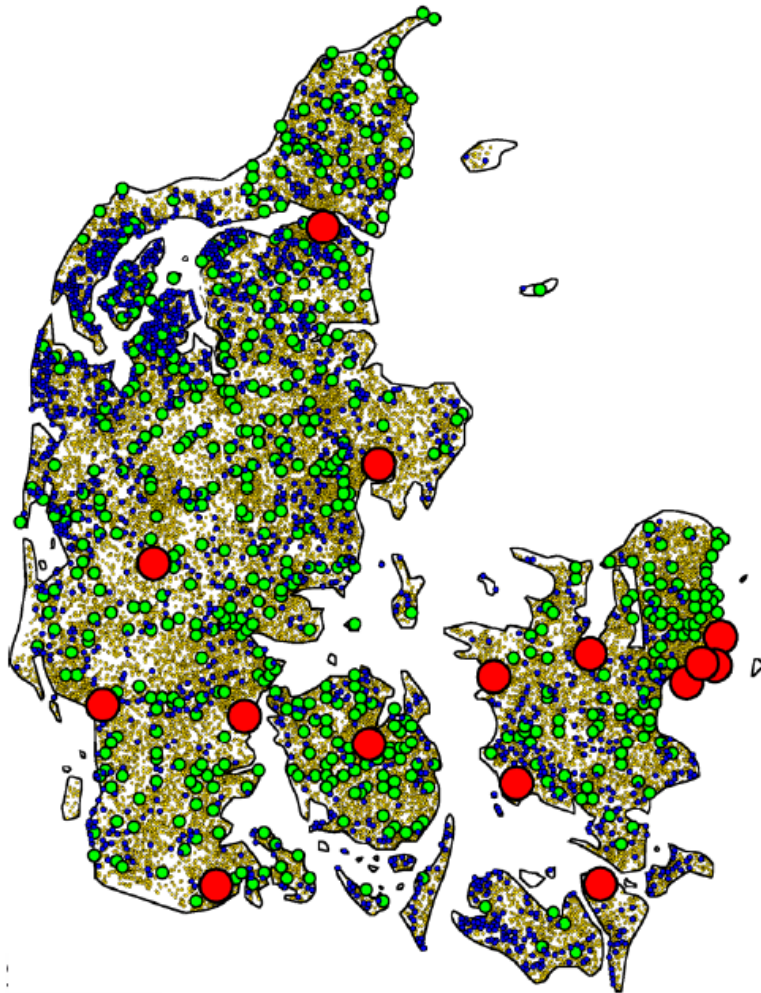


**Consumption**

**Flexibility** can be provided by several means:

- Supporting grids (Transmission / Production)
- **Flexible/intelligent consumption –Time shifting**
- Energy storage

# Introduction: Distributed Small Energy Resources



## Year 2025:

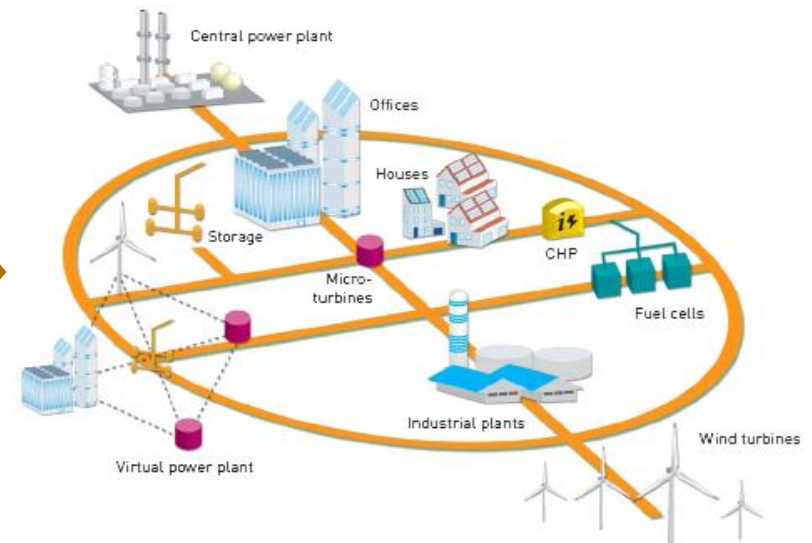
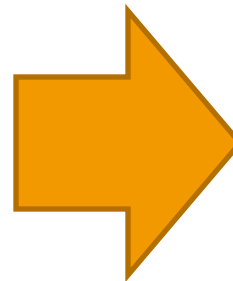
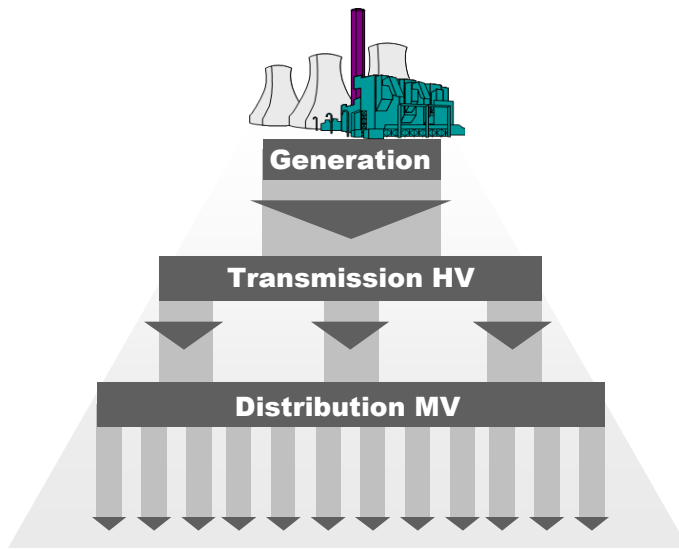
- 15 central power plants
- 500 local CHP plants
- 6.000 wind turbines ( 50% of energy)
- 1.000.000 small energy resources  
(households, electrical vehicles, industrial consumers)

- Distributed small energy resources need to participate in the provision of ancillary services.
- **Active** load management
- Energy efficiency

Smart grids - Active control of distributed resources



# Challenges of the Future Energy System



## Present Energy System

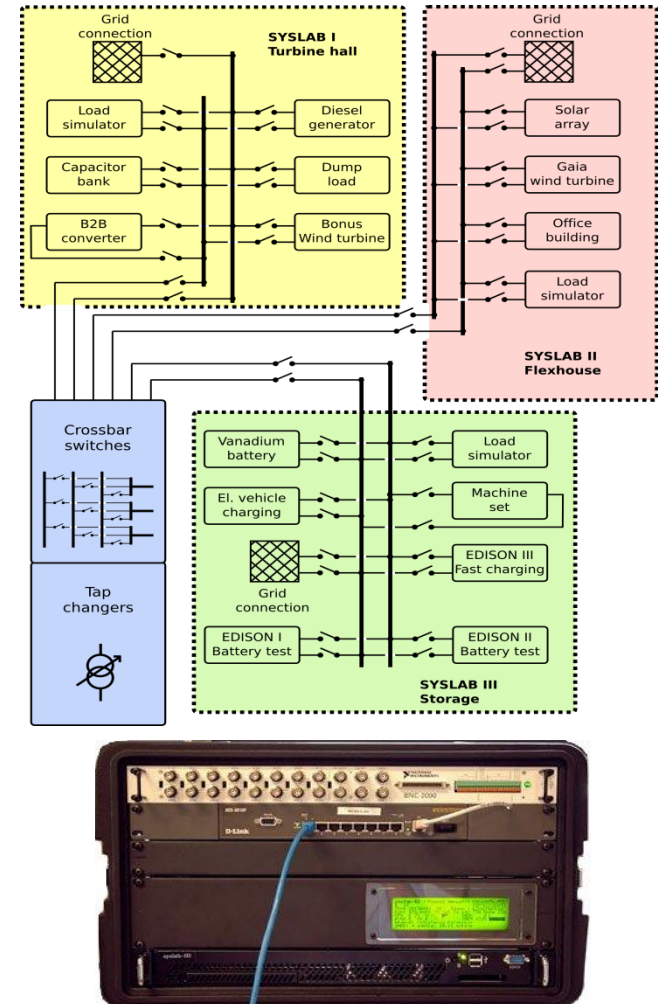
- Production follows load

## Future Energy system:

- Consumption follows production

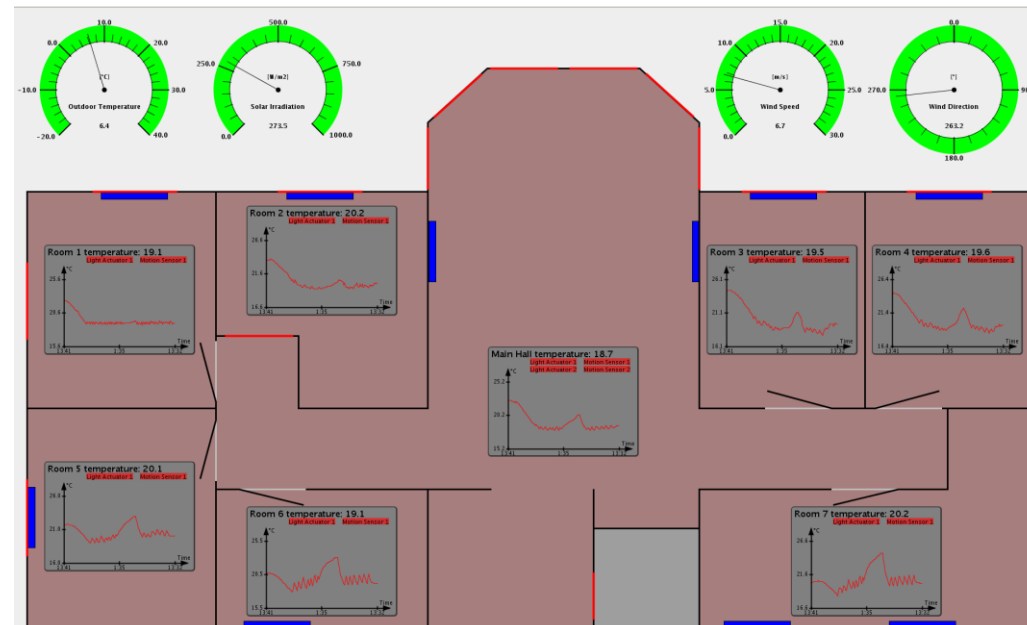
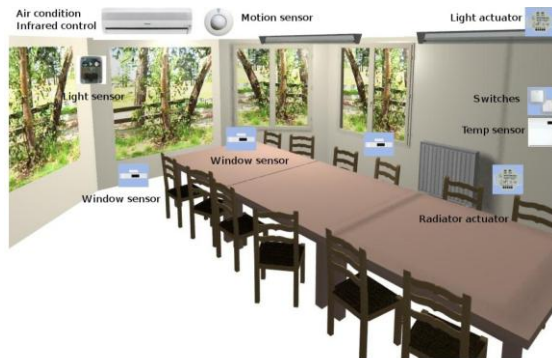


# SYSLAB-Distributed Power System Laboratory



# PowerFlexhouse-Intelligent office building

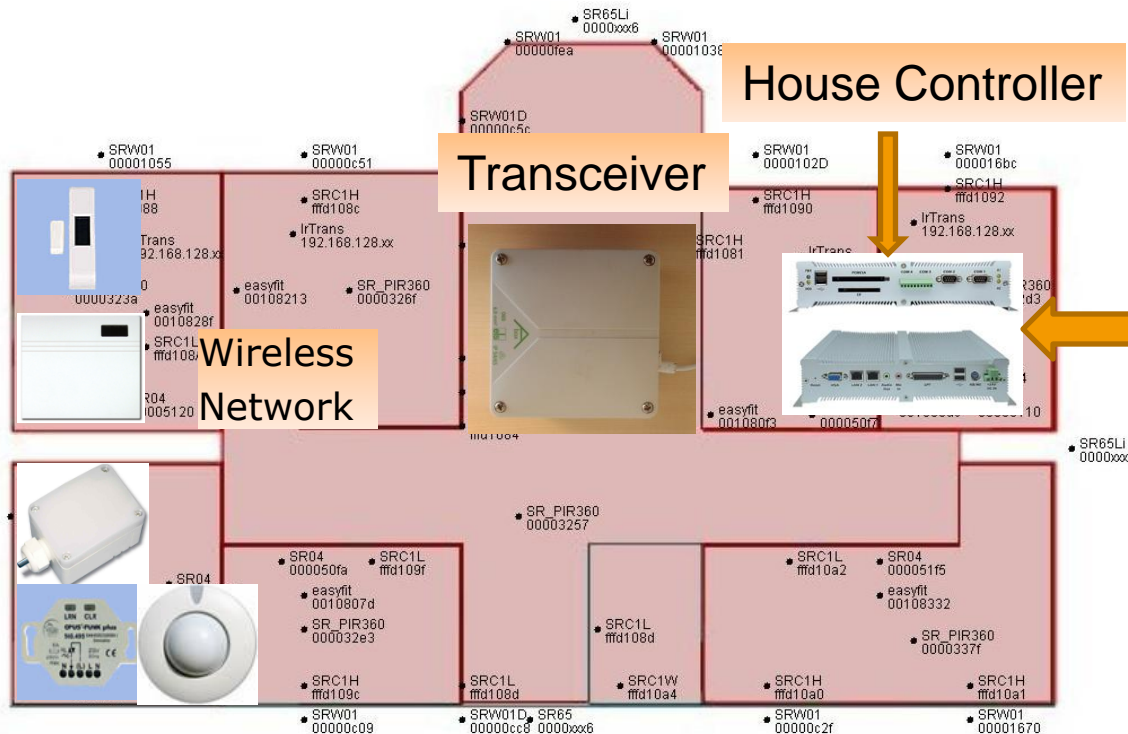
- Active load management
- Many individually controllable loads
  - Heaters
  - Air conditioners
  - Water heater, coffee machine, etc.
- Many sensors
  - Motion
  - Temperature
  - Door/Window
  - Solar irradiation
  - Wind speed
- Actuators and switchers, etc.



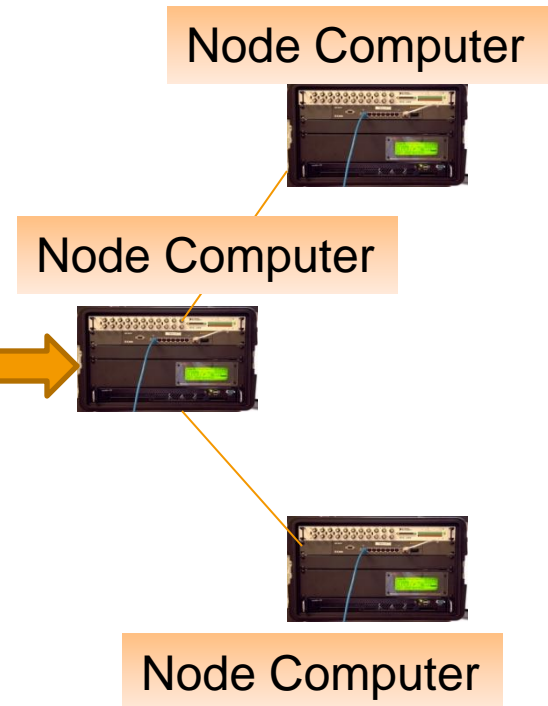


# Hardware Infrastructure

- PowerFlexHouse

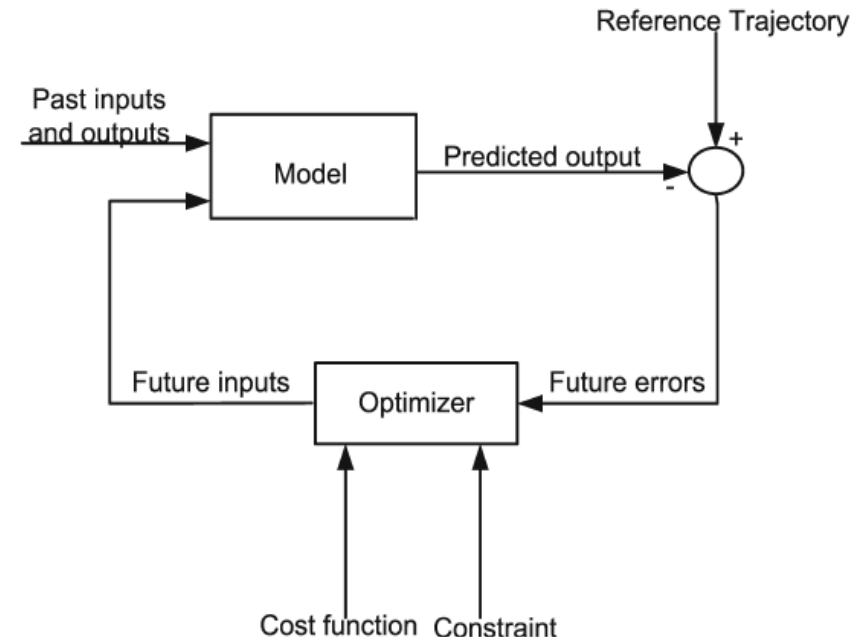
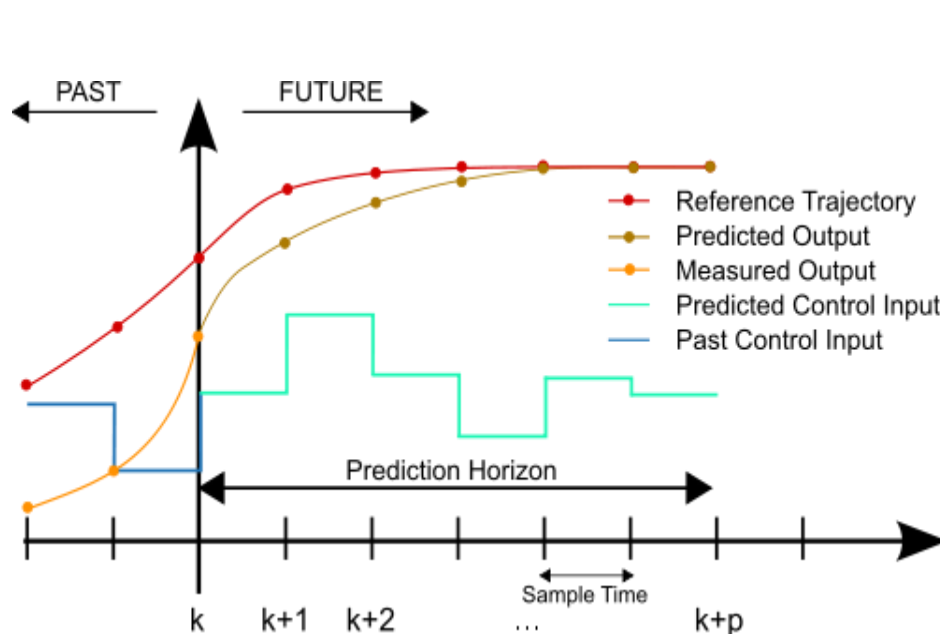


- SYSLAB Network



# What is **M**odel **P**redictive **C**ontrol ?

**MPC** refers to a class of control algorithms that compute a sequence of manipulated variable adjustments to keep the reference trajectory by utilizing a process model to optimize forecasts of process behaviour based on a linear or quadratic open-loop performance objective, subject to equality or inequality constraints over a future time horizon.

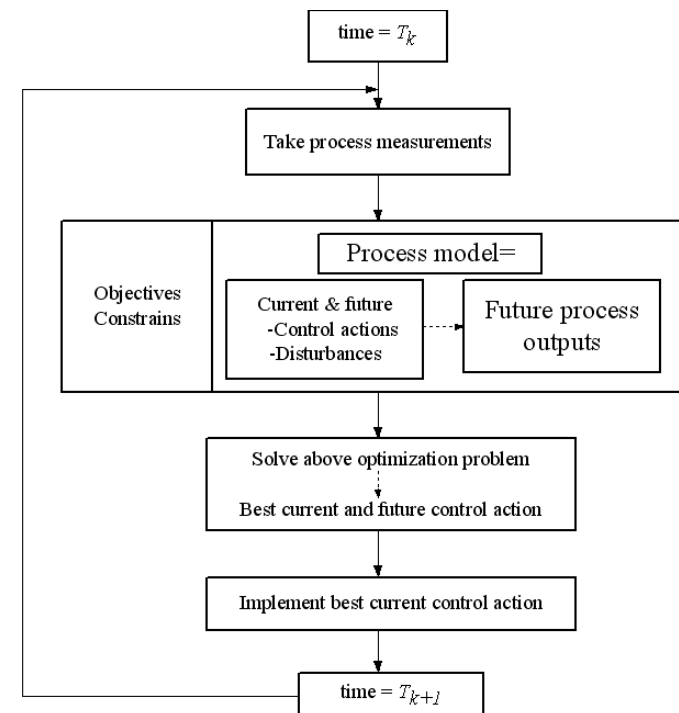
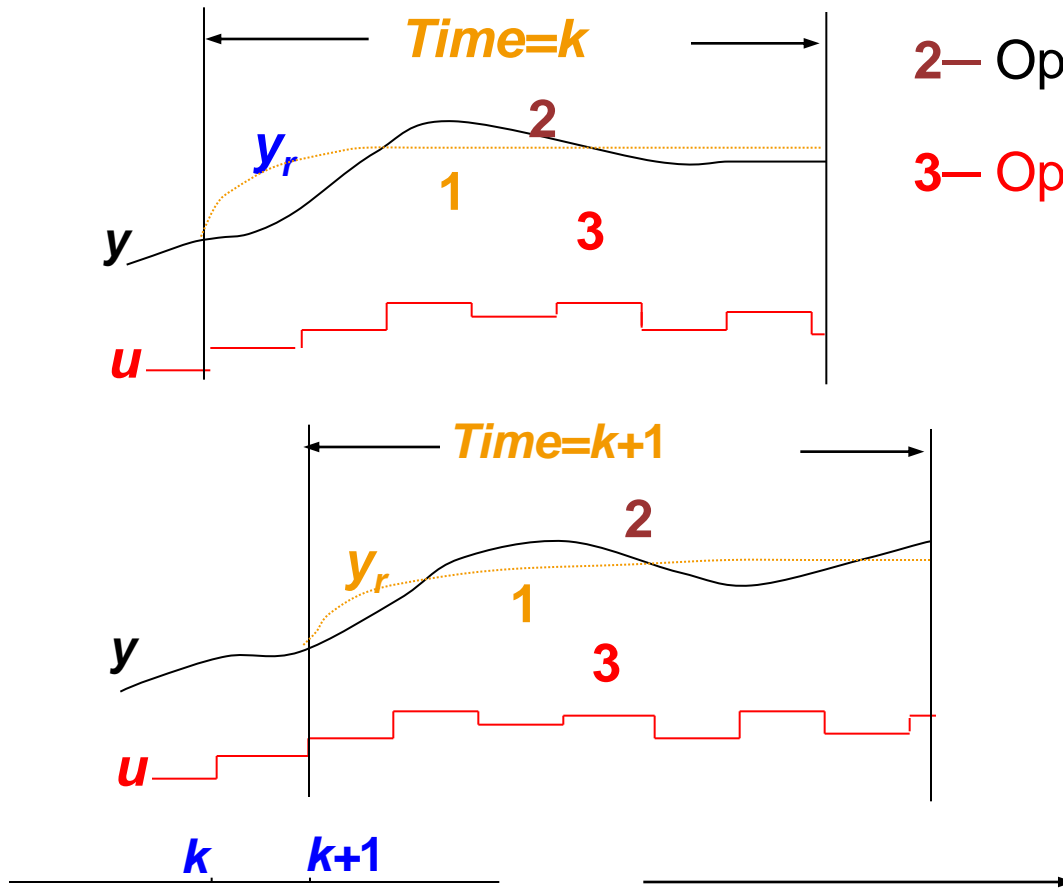


# MPC Strategy=Receding Horizon Control

1— Reference trajectory  $y_r$

2— Optimal predictive output  $y$

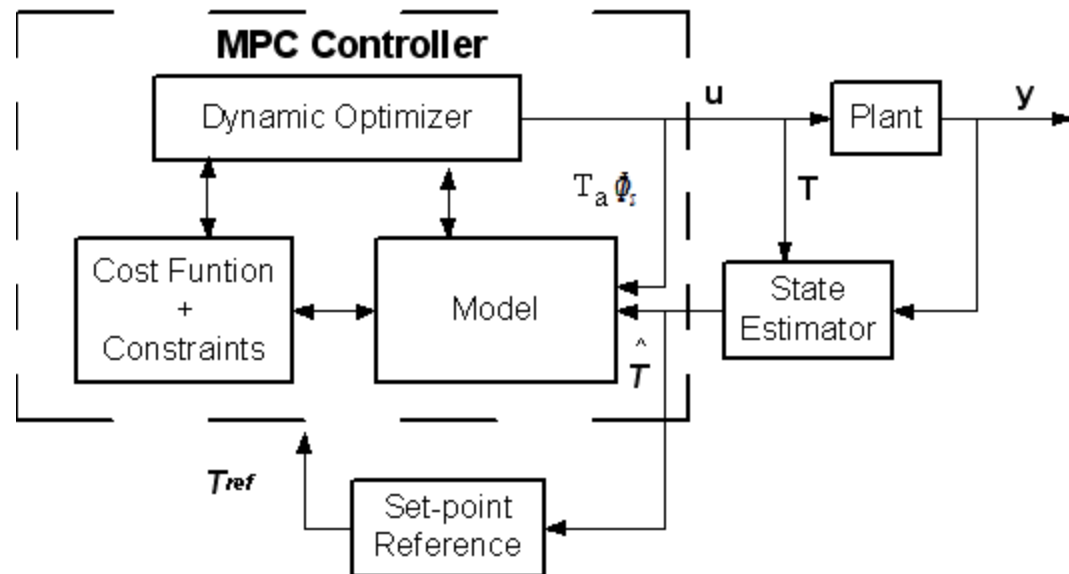
3— Optimal control action  $u$



# Model Predictive Controller (MPC) for Flexhouse's Heaters—Load shifting

## Components of MPC

- Prediction model
- Objective function
- Obtaining the control law



# Discrete-time linear state-space model

[Anders Thavlov]

$$\mathbf{T}(t + 1) = \Phi \mathbf{T}(t) + \Gamma \mathbf{U}(t) \quad (1)$$

Output:  $\mathbf{y}(t) = \mathbf{C} \mathbf{T}(t) = [1 \ 0 \ 0] \begin{bmatrix} T_i(t) \\ T_{im}(t) \\ T_{om}(t) \end{bmatrix} \quad (2)$

where

$$\Phi = \begin{bmatrix} 9.9288 \times 10^{-1} & 1.8661 \times 10^{-4} & 5.6429 \times 10^{-3} \\ 2.7410 \times 10^{-1} & 7.2489 \times 10^{-1} & 8.1923 \times 10^{-4} \\ 1.5641 \times 10^{-4} & 1.5459 \times 10^{-8} & 9.9649 \times 10^{-1} \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} 1.2844 \times 10^{-3} & 2.9990 \times 10^{-2} & 1.0226 \times 10^{-2} \\ 1.8592 \times 10^{-4} & 2.6053 \times 10^2 & 1.4838 \times 10^{-3} \\ 3.3551 \times 10^{-3} & 1.6128 \times 10^{-6} & 8.0402 \times 10^{-7} \end{bmatrix}$$

$\mathbf{T} = [T_{in} \ T_{im} \ T_{om}]$  is the state vector and  $\mathbf{U} = [T_a \ \phi_s \ \phi_h]$  is the input vector to the system.



# Objective function

$$J = \min [\sum_{k=0}^{H_p-1} C(k) \times \mu(k) + \sum_{k=0}^{H_p-1} w(|T_{in}^k - T_{ref}|)^2]$$

- Constrains:
  - minimum indoor temperature  $T_{in\_min} = 19.5 \text{ } ^\circ\text{C}$
  - maximum indoor temperature  $T_{in\_max} = 22.5 \text{ } ^\circ\text{C}$
  - reference indoor temperature  $T_{ref} = 21.5 \text{ } ^\circ\text{C}$

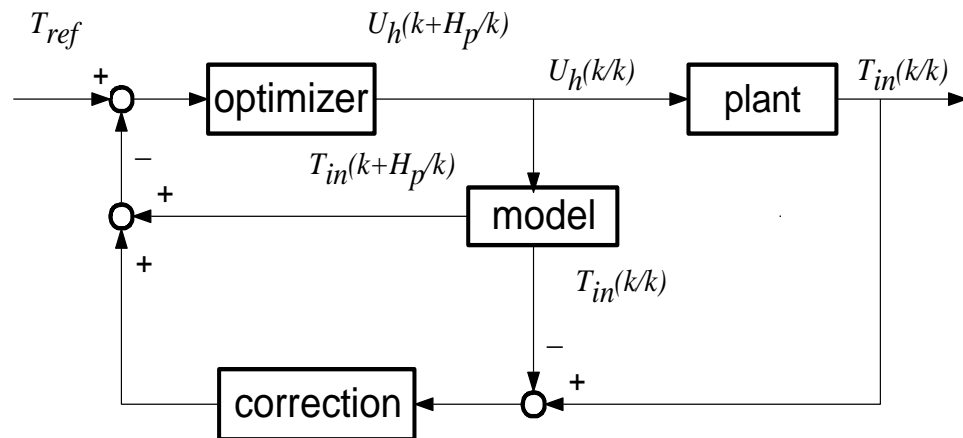
$C(k)$  is the dynamic power price signal.

$\mu(k) \in \text{int } [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]$ , which means the heat inputs that the MPC heat controller determines by **mixed integer optimization approach**.

$$\begin{aligned} & \min_{\Delta\mu_0, \dots, \Delta\mu_{N-1}} \sum_{k=0}^{N-1} \|C_k \Delta\mu_k\|_p + \|w(y_k - y_{ref})\|_p \\ & \text{s.t. } x_0 = x(0) \\ & \quad x_{k+1} = Ax_k + B\mu_k \\ & \quad y_k = Cx_k \\ & \quad x_k \in X \\ & \quad y_k \in Y \\ & \quad \mu_k \in U \end{aligned}$$

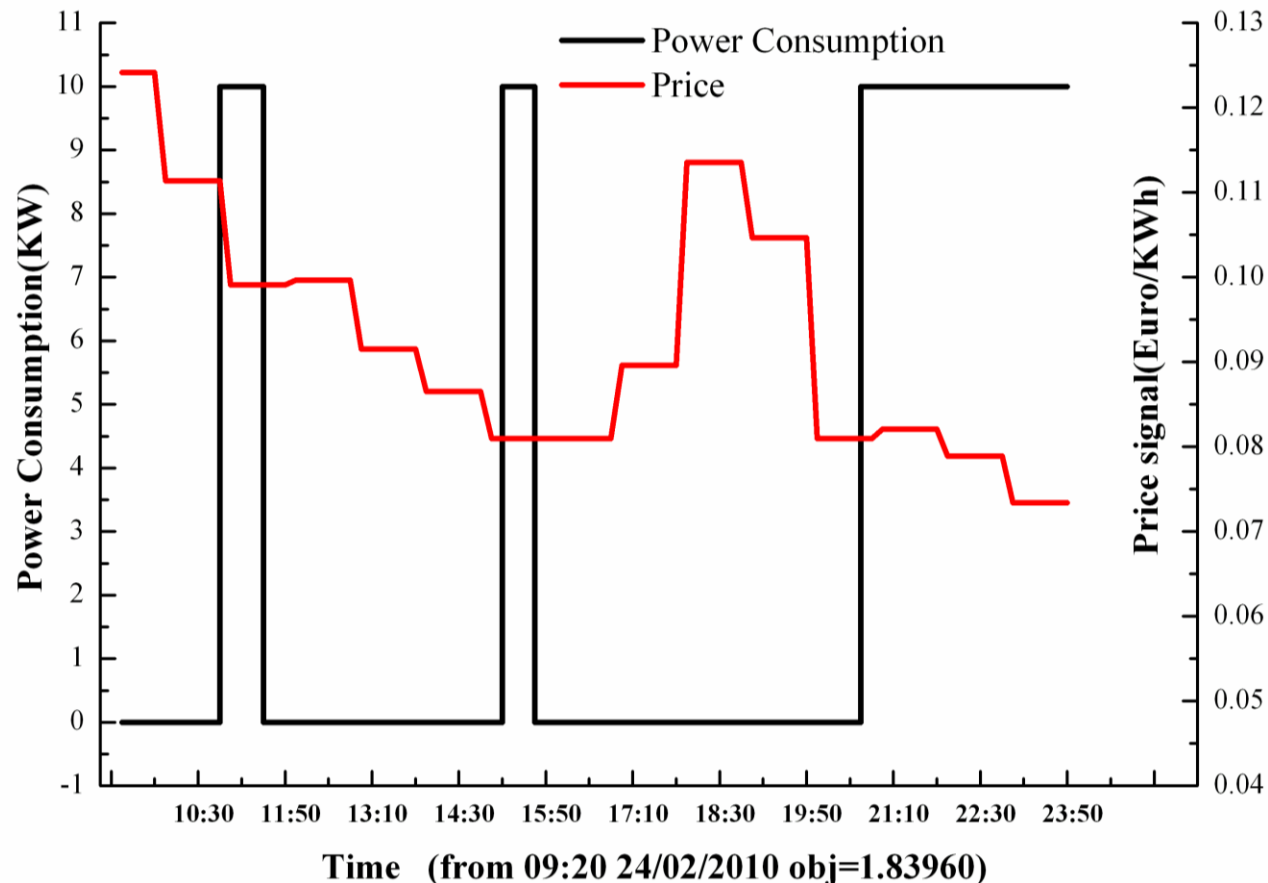
# Tools

- Dynamic power price signal:  
<http://www.nordpoolspot.com/reports/systemprice>
- **GNU Linear Programming Kit (GLPK Java)** ver 4.39
- *Java Matrix Package: **JAMA***



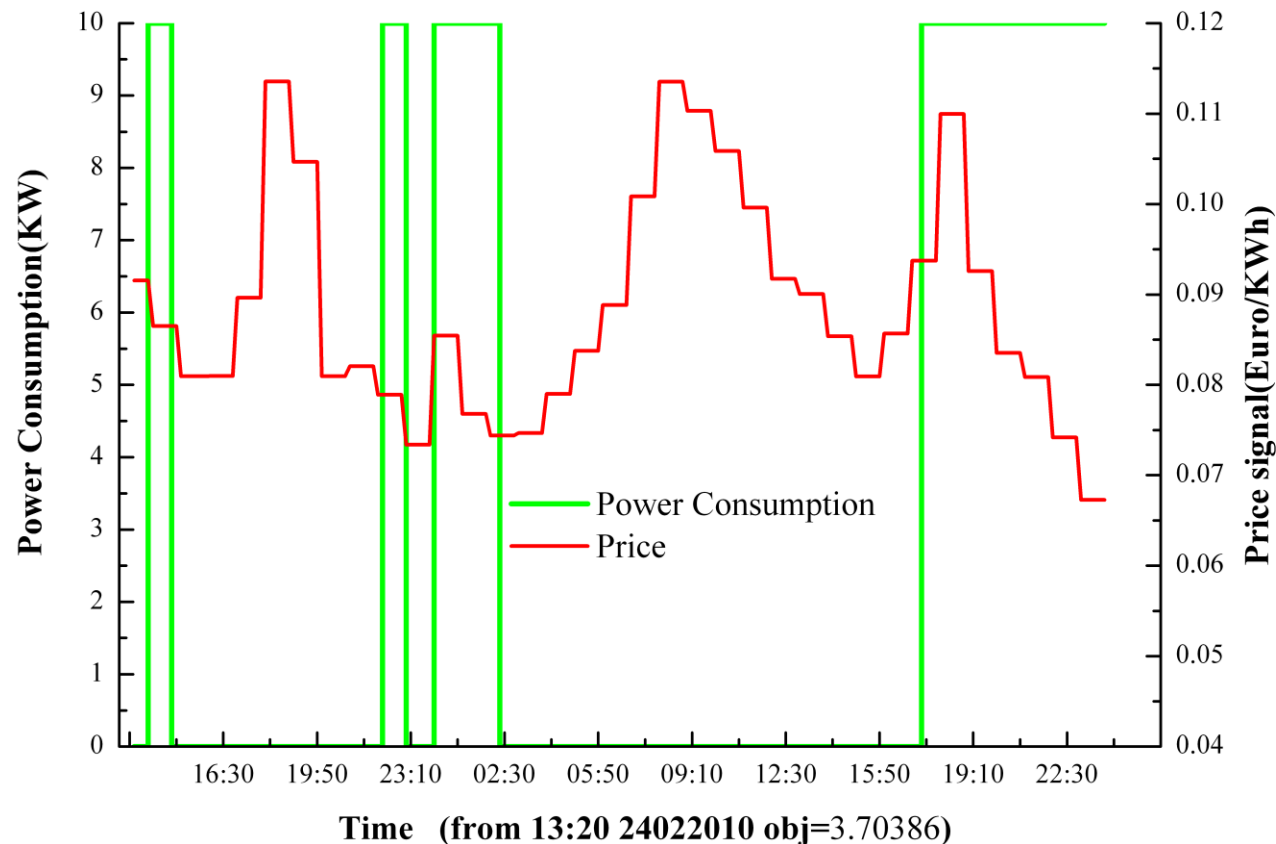
# Results: no weather forecast data

- Optimized predictive power consumption for the next 15 hours



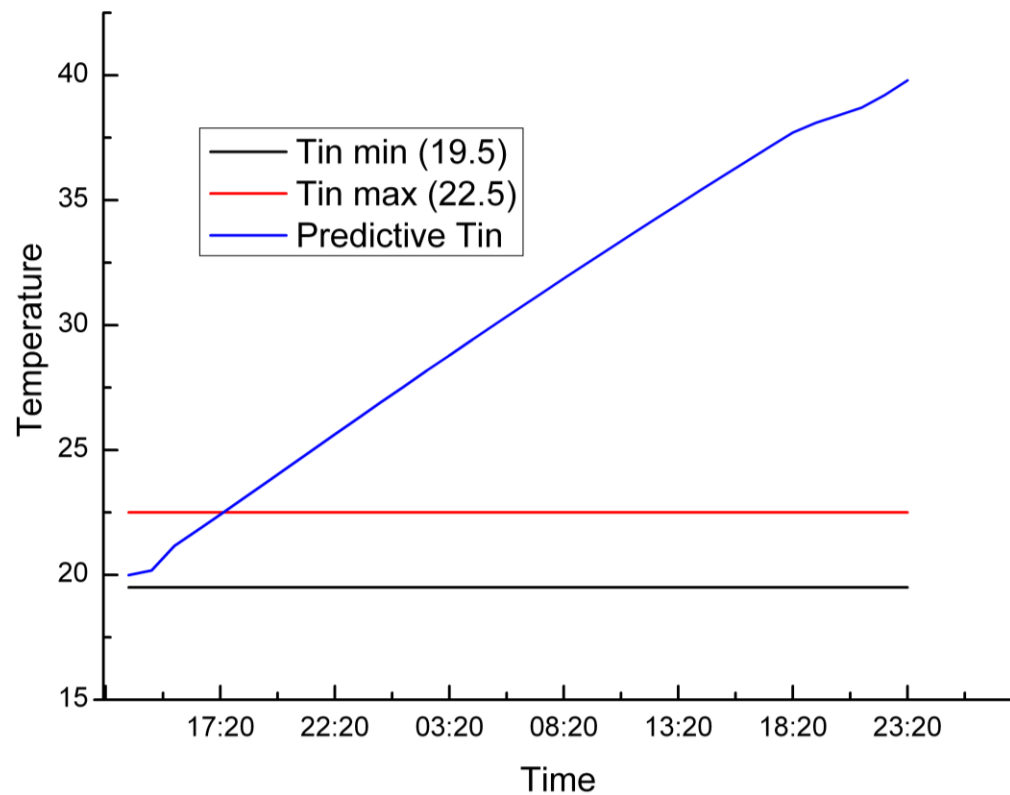
# Results: no weather forecast data

- Optimized predictive power consumption for the next 35 hours



# MPC: model??

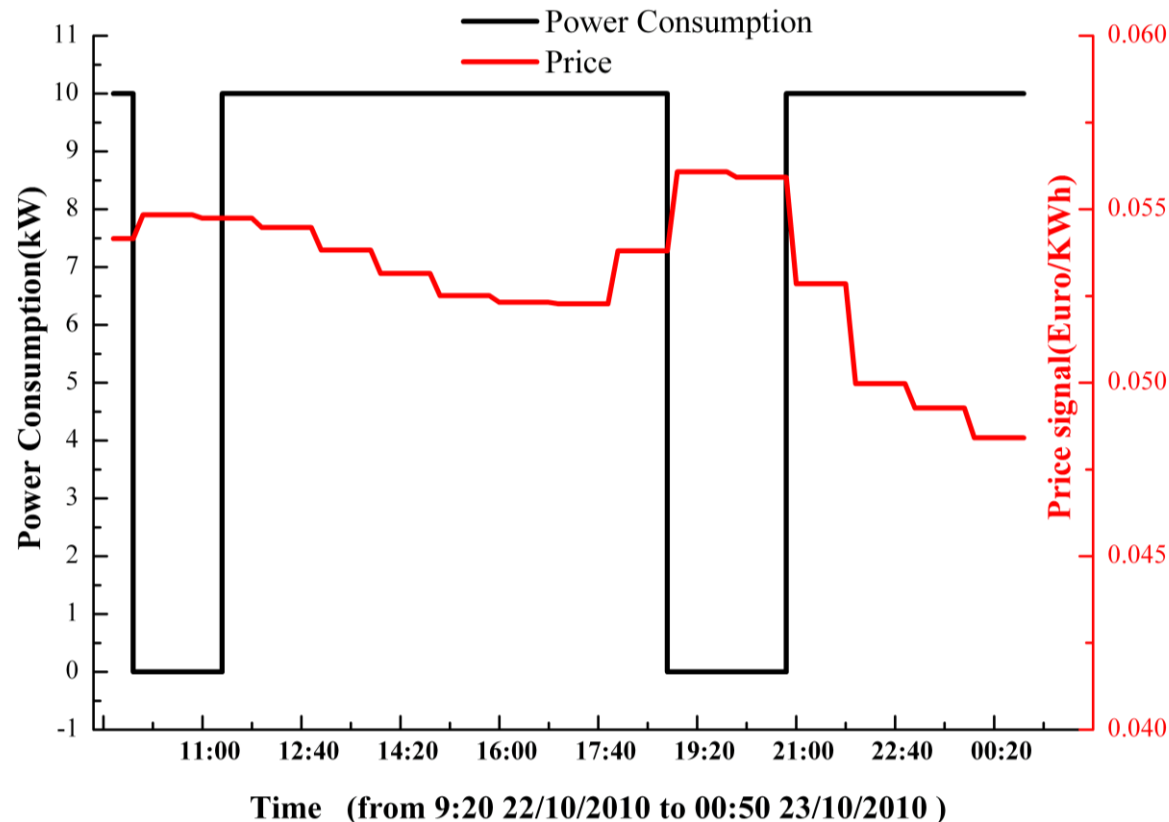
- Predictive Temperature ???





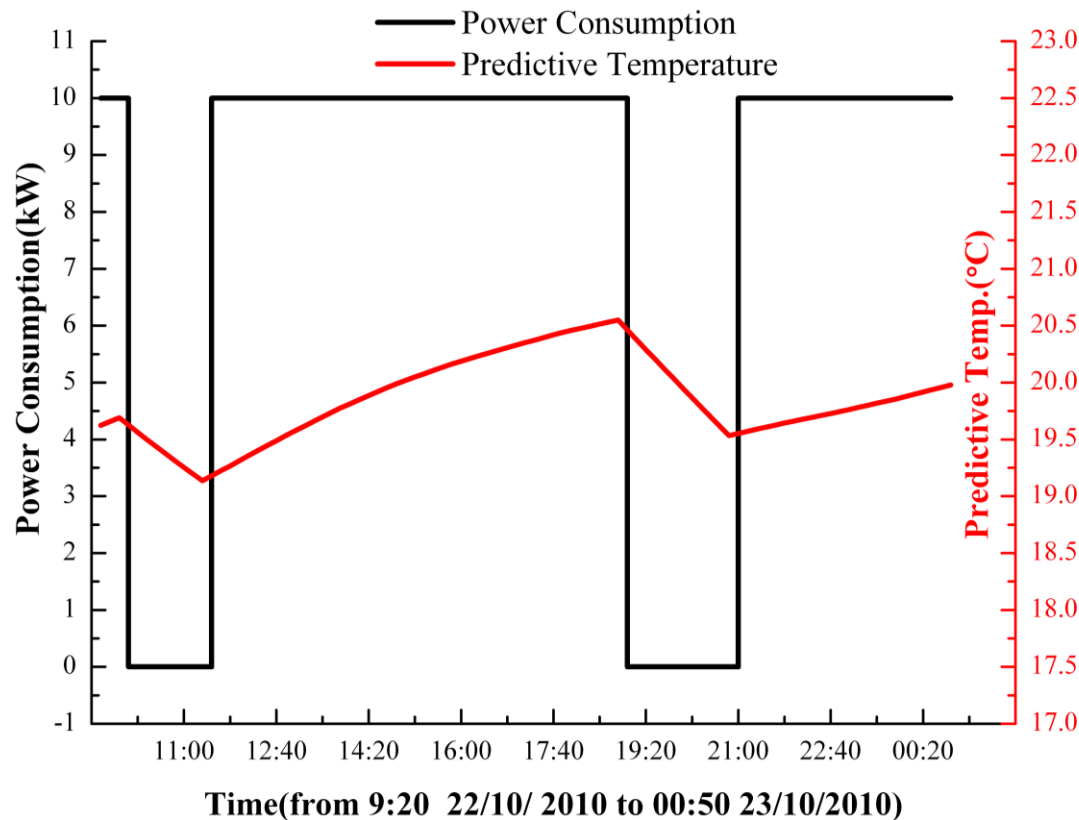
# Results: Integrate VEA weather forecast data

Optimized predictive power consumption in the next 15 hours



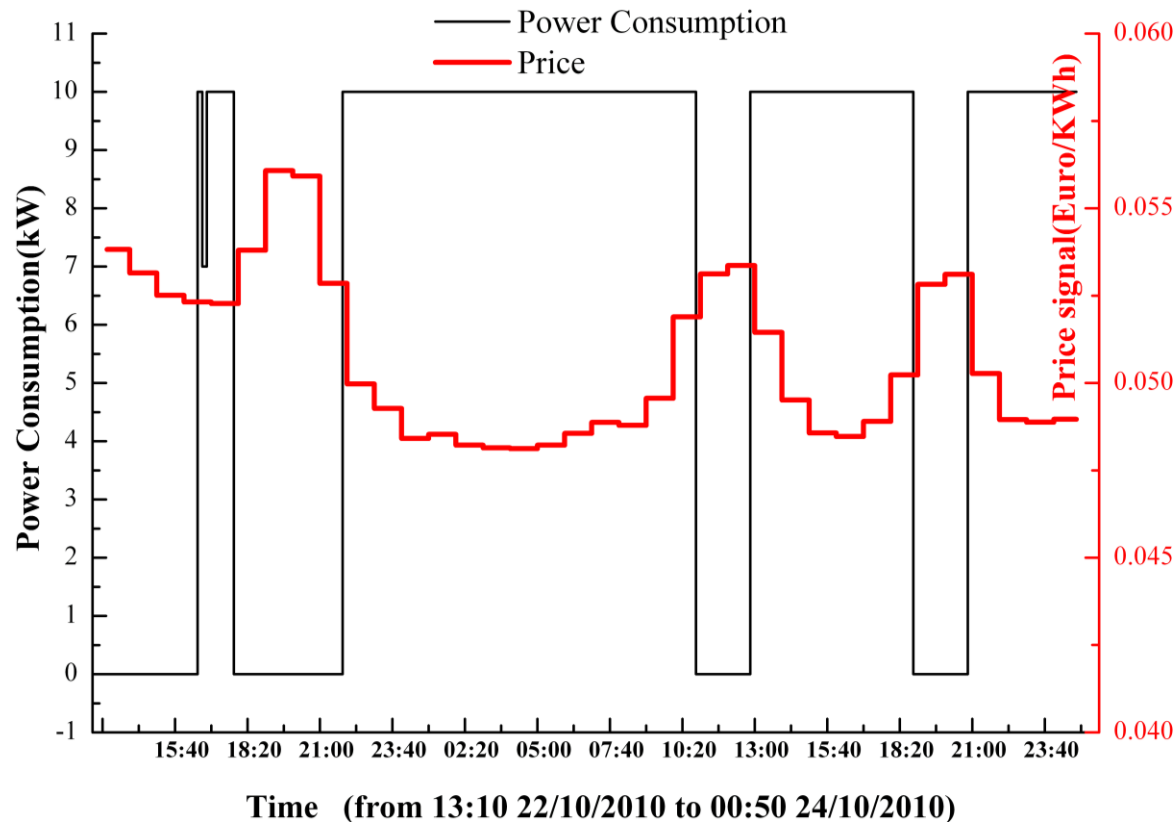
# Results: Integrate VEA weather forecast data

Predictive inside temperature in the next 15 hours



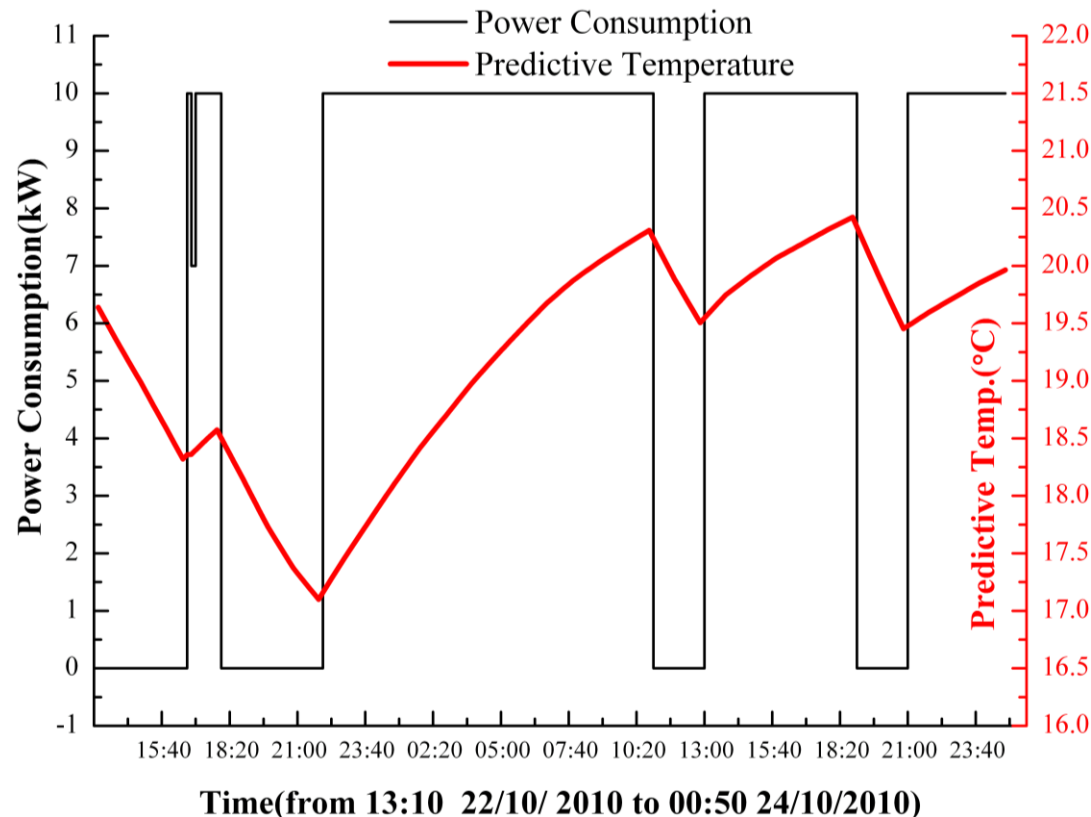
# Results: Integrate VEA weather forecast data

Optimized predictive power consumption in the next 35 hours



# Results: Integrate VEA weather forecast data

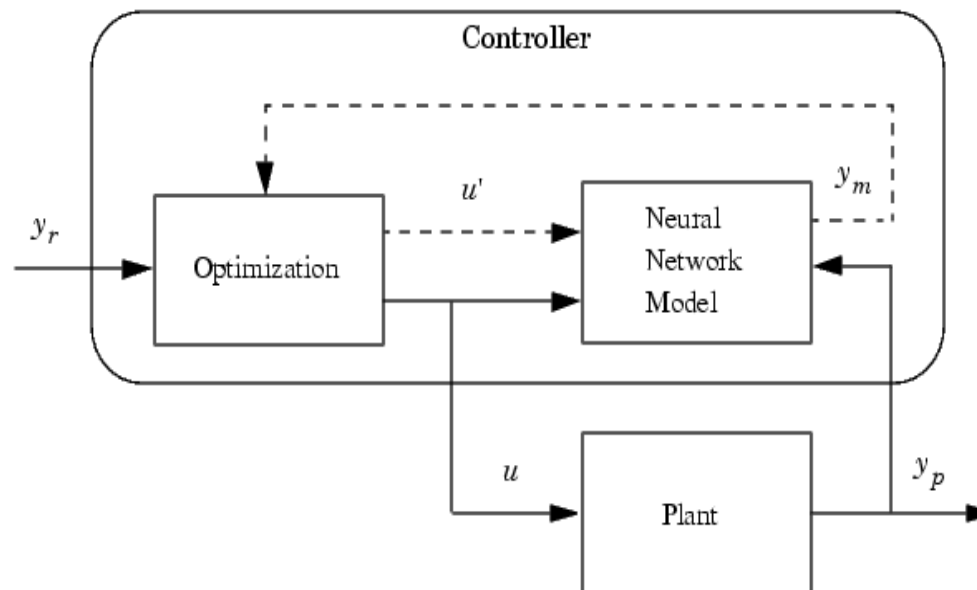
Predictive inside temperature in the next 35 hours



# Future work

- Comparison with different control strategy ( thermostat operation)
- User Interface
- Nonlinear optimization

Objective function / Quadratic optimization  
 NN Predictive Control for nonlinear model





# Conclusions

- It is clearly demonstrated that the MPC strategy is feasible for load management of intelligent houses in a distributed power system with high wind penetration.
  - The predictive control effect depends on the prediction horizon.
  - Model plays a very important role.
- It also shows that various control strategies and theories can be investigated on load management and also on how this intelligent house, which is used to stabilize fluctuations in the power grid with a high penetration of renewable energy, in comparison with the actual power system presented within the SYSLAB.
- The load in a power grid is widely seen as one of the keys to achieving additional operational flexibility to ensure the stability of the grid as penetration levels rise. However, the efficient use of load management demands a tight integration with the control system of the power grid.
- Residential customers can avoid high electricity price charge at peak time, and the power grid can benefit from load control.



# Acknowledgement

- Daniel kullmann
- Anders Thavlov
- Oliver Gehrke
- Henrik Bindner
  
- Andrea Hahman

# Thank you!

